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VIBRATION-BASED DAMAGE DETECTION IN ROTATING MACHINERY

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Abstract: Damage detection as determined from changes in the vibration characteristics of a system has been a popular research topic for the last thirty years. Numerous damage identification algorithms have been proposed for detecting and locating damage in structural and mechanical systems. To date, these damage-detection methods have shown mixed results. A particular application of vibration-based damage detection that has perhaps enjoyed the greatest success is that of damage detection in rotating machinery. This paper summarizes the state of technology in vibration-based damage detection applied to rotating machinery. The review interprets the damage detection process in terms of a statistical pattern recognition paradigm that encompasses all vibration-based damage detection methods and applications. The motivation for the study reported herein is to identify the reasons that vibration-based damage detection has been successfully applied to rotating machinery, but has yet to show robust applications to civil engineering infrastructure. The paper concludes by comparing and contrasting the vibration-based damage detection applied to rotating machinery with large civil engineering infrastructure applications.

1. INTRODUCTION

Vibration-based damage detection for rotating machinery (RM) has been repeatedly applied with success to a variety of machinery elements such as roller bearings and gears. In the past, the greatest emphasis has been on the qualitative interpretation of vibration signatures both in the frequency and (to a lesser extent) in the time domain. Numerous summaries and reviews of this approach are available in textbook form, including detailed charts of machinery fault analysis, e.g., see [1]-[6]. The approach taken has generally been to consider the detection of damage qualitatively on a fault-by-fault basis by examining acceleration signatures for the presence and growth of peaks in spectra at certain frequencies, such as multiples of shaft speed. A primary reason for this approach has been the inherent nonlinearity associated with damage in RM. Recently, more general approaches to damage detection in RM have been developed. These approaches utilize formal statistical methods to assess both the presence and level of damage on a statistical basis, e.g., see [7] and [8]. A particularly detailed and general treatment of mechanical signature analysis is presented in [9].

In this review, the damage detection process for RM is posed in terms of a statistical pattern recognition paradigm that encompasses all vibration-based damage detection methods and applications. For RM the qualitative methods of vibration signature interpretation cited above primarily fall into the category of non-model-based pattern recognition, in that the identification of damage is based only on changes in recorded vibration signatures. Although not discussed in this summary, many of the cited references list typical vibration characteristics of machine faults at the machine and component (bearing, gear, etc.) level and provide physical explanations for these characteristics.

The study reported herein was motivated by two considerations. First, the authors are investigating applications of vibration-based damage detection to systems that, although not rotating, can not be instrumented on their interior. Second, the authors have been involved in several studies of damage detection in large civil engineering infrastructure. These studies and other similar studies reviewed from the technical literature have shown mixed results, at best [10]. Therefore, this study was undertaken to identify the aspects of the RM applications that have allowed vibration-based damage detection to exhibit a high degree of success and to become a standard practice for this industry. This paper concludes by comparing and contrasting the RM application of vibration-based damage detection to the large civil engineering structures application.

2. THE DAMAGE DETECTION PROCESS

In the context of statistical pattern recognition the process of vibration-based damage detection can be broken down into four parts as summarized in Fig. 1. The topics summarized in this flow chart are briefly discussed below.

2.1. Operational Evaluation

An *operational system* is here defined to be one that can perform or is performing its intended function. *Operational evaluation* attempts to answer three questions regarding the implementation of a damage identification investigation:

1. How is damage defined for the system being investigated and, for multiple damage possibilities, which cases are of the most concern?
2. What are the conditions, both operational and environmental, under which the system to be monitored functions?
3. What are the limitations on acquiring data in the operational environment?

Operational evaluation begins to set the limitations on what will be monitored and how the monitoring will be accomplished. This evaluation starts to tailor the damage detection process to features that are unique to the system being monitored and tries to take advantage of unique characteristics of the damage that is to be detected.

2.2 Data Acquisition and Cleansing

The data acquisition portion of the health monitoring process involves selecting the types of sensors to be used, the location where the sensors should be placed, the number of sensors to be used, and the data acquisition/storage/transmittal hardware. Again, this process will be application specific. Another consideration is how often the data should be collected.

Because the data can be measured under different conditions, the ability to normalize the data may be important to the damage detection process. When environmental variability is an issue, the need can arise to normalize the data in some temporal fashion to facilitate the comparison of data measured at similar times of an environmental cycle.

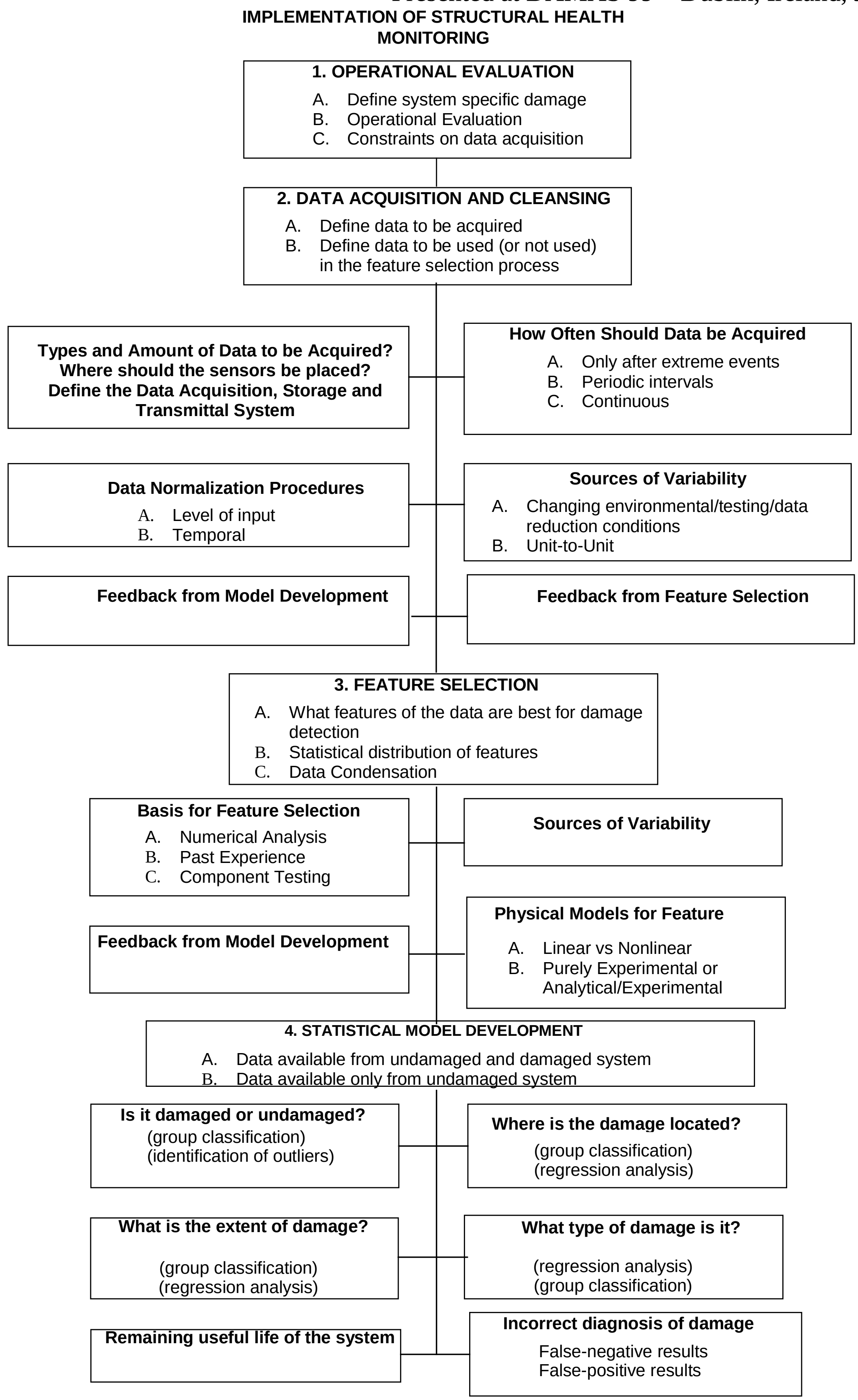

Fig. 1 Flow Chart for Implementing a Damage Detection/Health Monitoring Program.

Sources of variability in the data acquisition process should be identified and minimized to the extent possible. In general, all sources of variability cannot be eliminated. Therefore, it will be necessary to make the appropriate measurements such that these sources can be statistically quantified.

Data cleansing is the process of selectively choosing data to accept for, or reject from, the feature extraction process. The data cleansing process is usually based on knowledge gained by individuals directly involved with the data acquisition.

Finally, it should be noted that the data acquisition and cleansing portion of a health-monitoring process should not be static. Insight gained from the feature selection process and the statistical model development process will provide information regarding changes that can improve the data acquisition process.

2.3 Feature Selection

The portion of the damage detection process that receives the most attention in the technical literature is the identification of data features that allow one to distinguish between the undamaged and damaged component or system. Inherent in this feature selection process is the condensation of the data. The best features for damage detection are typically application specific.

A variety of methods are employed to identify features for damage detection. Past experience with measured data from a system, particularly if damaging events have been previously observed for that system, is often the basis for feature selection. Numerical simulation of the damaged system's response to simulated inputs is another means of identifying features for damage detection. The application of engineered flaws, similar to ones expected in actual operating conditions, to specimens can identify parameters that are sensitive to the expected damage. Damage accumulation testing, during which significant structural components of the system under study are subjected to a realistic accumulation of damage, can also be used to identify appropriate features. Fitting linear or nonlinear, physical-based or non-physical-based models of the system response to measured data can also help identify damage-sensitive features.

The operational implementation and diagnostic measurement technologies needed to perform health monitoring often produce a large amount of data. A condensation of the data is advantageous and necessary particularly if comparisons of many data sets over the lifetime of the structure are envisioned. Also, because data may be acquired from a structure over an extended period of time and in an operational environment, robust data reduction techniques must be developed to retain sensitivity of the chosen features to the structural changes of interest in the presence of environmental noise. To further aid in the recording of quality data and feature extraction needed to perform the structural damage detection process, the statistical significance of the data changes should be characterized and used in the condensation process.

2. 4. Statistical Model Development

The portion of the health monitoring process that has received the least attention in the technical literature is the development of statistical models to enhance the damage detection process. Statistical model development is concerned with the implementation of the algorithms to operate on the extracted features and unambiguously determine the damage state of the structure. The algorithms used in statistical model development usually fall into three categories and will depend on the availability of data from both an undamaged and damaged component or system. The first category is *group classification*, that is, placement of the data into respective “undamaged” or “damaged” categories. *Analysis of outliers* is the second type of algorithm. When data from a damaged system are not available for comparison, do the observed features indicate a significant change from the previously observed features that cannot be explained by extrapolation of the feature distribution? The third category is *regression analysis*. This analysis refers to the process of correlating data features with particular types, locations or extents of damage. All three algorithm categories analyze statistical distributions of the measured or derived features to enhance the damage detection process.

The damage state of the system could be described as a five-step process along the lines of the four-step process discussed in [11] and answers the following questions: 1. Is there damage in the system (existence)?; 2. Where is the damage in the system (location)?; 3. What kind of damage is present (type)?; 4. How severe is the damage (extent)?; and 5. How much useful life remains (prediction)? The steps in the process also represent increasing knowledge of the damage state. This process usually requires that data from the specific types of damage are available to be correlated with the observed features.

Finally, an important part of the statistical model development process is the testing of these models on actual data to establish the sensitivity of the damage detection and to study the possibility of false indications of damage. False indications of damage fall into two categories: 1.) *False-positive* damage indication (indication of damage when none is present), and 2). *False-negative* damage indications (no indication of damage when damage is present). Although the second category is usually very detrimental to the damage detection process, false-positive readings can also erode confidence in the damage detection process. This paper will now summarize the state of technology in vibration-based damage detection as applied to RM by interpreting this damage detection application in terms of the statistical pattern recognition paradigm.

3. OPERATIONAL EVALUATION FOR RM

The definition of damage is often very straightforward for RM. Often, there are a limited number of damage scenarios that are being monitored and the possible locations of that damage are known *a priori*. The primary operational limitation on acquiring data is that the machine will typically be in operation and performing its normal function or will be in a transient start-up or shutdown mode. In its *in situ* environment many other machines will most likely produce additional vibration sources that must be accounted for in the damage detection process. Limitations to acquiring vibration data can vary widely. For many applications the limitations will be based on administrative criteria such as the availability of personnel to make the necessary measurements. In other applications the machine may be located in hazardous environments allowing for only limited access time.

4. DATA ACQUISITION FOR RM

Data acquisition issues for RM include the type of sensor and number of sensors that should be used, the location where these sensors should be placed, how the sensors should be mounted, environmental effects on the sensors, how the signals from these sensors should be recorded, for what duration and how often the signals should be recorded, and what type of averaging and windowing should be applied to the signals. Also, what steps can be taken to make the data acquisition as repeatable as possible. Finally, what are the necessary measurements that will allow one to quantify the uncertainty in the data acquisition process.

Data acquisition transducers and recording equipment used to monitor RM are discussed in detail in References [1]-[6]. The selection and placement of appropriate transducers depends upon the type of machinery and its construction. Further, the appropriate placement of transducers is discussed in detail in [4].

The primary vibration transducer used for damage detection and condition monitoring of RM is the accelerometer. Piezoelectric accelerometers have a broad operating frequency range and are well suited to monitoring of roller bearings and gear trains. Accelerometers are typically used in conjunction with single-channel signal analyzers so that the machinery vibration output signal can be viewed in the frequency domain as well as a function of time, i.e., amplitude-frequency, amplitude-time, and waterfall plots. Velocity transducers and non-contact displacement transducers are also widely used. Non-contact (Eddy current) displacement transducers find application in the monitoring of shaft motion and position relative to fluid-film bearings. A set of two transducers, mounted at right angles, is often used to determine the orbit of the shaft in its bearing.

5. FEATURES USED TO IDENTIFY DAMAGE IN RM

There exist numerous detailed charts of anticipated characteristic faults of a variety of machines and machine elements (e.g., see the chart on pp.515-522 in [1]; or the charts on pp. 88-92 in [2, Vol.1]). Features are those parameters derived from the measured data that robustly indicate the presence of these faults. Features might be partitioned into two categories: Qualitative Features and Quantitative Features. Qualitative features would include the classical indicators of damage such as listed in rotating machinery diagnostic charts (e.g., see References [1]-[6]). The most complete chart appears to be that in Reference [1]. This chart is updated semi-annually and is commercially available. While labeled “qualitative”, these features have in fact been widely used to successfully detect the presence, location (e.g., roller bearing as opposed to gear trains), type of fault (e.g., outer race damage), and degree of damage. Commercially available software specifically designed for the isolation of faults based on vibration signatures is readily available. For example, an automated, expert diagnostic system is evaluated in [12].

Qualitative features include, for example, the presence of peaks in acceleration spectra at certain multiples of shaft rotational frequency and their growth or change with time. The important qualitative features are quite distinct to the type of machine element, the specific fault, and in some cases to the level of damage. Therefore, it may be possible to locate the defective machine element (bearing, gears, etc.), isolate the specific fault in the element, and determine the level of damage (or remaining life) based purely on these qualitative features. Quantitative features used to date have some of the same characteristics as qualitative features: Detection of each fault is fundamentally different. Recent progress has, however, been reported [7] on generalized failure prediction indices capable of monitoring the condition of a wide variety of manufacturing equipment.

Quantitative features could be further broken down into the following categories: time-domain methods, transformed-domain methods, and time-frequency methods. Included in transformed-domain methods are the well-known frequency-domain methods as well as cepstrum (transform of a transform, specifically the inverse Fourier transform of the logarithm of the Fourier spectra magnitude squared) techniques. Briefly, frequency domain methods characterize changes in machine vibrations over a given time window. Time domain and time-frequency methods have application to non-stationary faults, i.e., those associated with machines that exhibit different phenomena in different phases of the machine cycle. Each of these methods is now briefly described.

5.1. Time Domain Methods

These methods have particular application to roller bearings, as roller bearings typically fail by localized defects caused by fatigue cracking and the associated removal of a piece of material on one of the contact surfaces of the bearing. Ref. [13] summarizes these methods (particularly for roller bearing analysis) as: peak amplitude, rms amplitude, crest factor analysis, kurtosis analysis, and shock pulse counting. As an example, Ref. [14] utilizes Kurtosis measurements in the detection of surface damage to machined surfaces, such as occurs in roller bearings, etc. Kurtosis is the fourth statistical moment of the data. If surface roughness attributes are used as an indicator of damage, then for a good surface, the profile is random corresponding to a Gaussian profile distribution with an infinite-sample theoretical value of 3.0. A Kurtosis value other than 3.0 denotes that the profile is no longer Gaussian, therefore indicating the presence of damage [14, 15]. Proprietary time-domain methods and associated instrumentation are commercially available for the detection of defects involving repetitive mechanical impacts, primarily associated with roller bearings [16].

5.2. Frequency Domain Methods

Approaches summarized in Ref [13] for roller bearings in this category include Fourier spectra of synchronized-averaged time histories, cepstrum analysis, sum and difference frequencies analysis, the high frequency resonance technique, and short-time signal processing. Quantitative evaluation of faults in gears using peaks in the cepstrum as indicators of harmonics is proposed in [17]. Thresholds distinguishing normal, moderate and serious wear in gears are determined quantitatively. Other cepstral approaches for spectral-based fault detection as applied to helicopter gearboxes are presented in [18].

5.3. Time-Frequency Methods

These methods have their application in the investigation of rotating machinery faults exhibiting non-stationary vibration effects. Non-stationary effects are associated with machinery in which the dynamic response differs in the various phases associated with a machine cycle. Examples include reciprocating machines, localized faults in gears, and cam mechanisms. The wavelet transform is discussed in [19] and is applied to fault detection and diagnosis of cam mechanisms in [20] and to a helicopter gearbox in [21]. An application to fault detection utilizing three widely differing methods falling in the above categories (Fourier transform, power cepstrum, and wavelet transform) as applied to two meshing spur gears with an induced local fault on one gear is shown in [22]. A comparative study of various quantitative features that fall into the time-domain and frequency-domain categories is presented in [23].

6. STATISTICAL MODELS APPLIED TO DAMAGE DETECTION IN RM

Once features have been selected and extracted from the data recorded on the RM, the next step is to infer whether or not damage is present, the type of damage, and possibly the level of that damage. This process can generally be described as a problem in pattern classification. Informally, skilled individuals can use their experience with previous undamaged and damaged systems and the changes in the features associated with previously observed damage cases to deduce the presence, type and level of damage. This is an example of the application of informal *supervised learning*. In this context supervised learning implies that examples of data from undamaged and damaged systems are available for analysis. For example, it is possible to examine acceleration signals in the frequency or time domain and deduce in some cases, from the presence and location of peaks, the type, location, and extent of damage of a rotating machinery component. As cited above, extensive tables are commercially available to facilitate this process.

More formal methods founded in machine learning have recently been introduced. These methods place the system of interest (as represented by one or more features) into either an undamaged category or one or more damaged categories [24]. The classification techniques fall into three general categories: Bayesian Classification, K^{th}-nearest neighbor rules, and artificial neural network classifiers [25]. A particularly powerful technique is that of artificial neural nets for statistical pattern classification [26]. As an illustration, artificial neural nets were used in Ref. [22] cited above for each of the three fault detection methods used to distinguish between "faulty" and "good" gears. Neural nets differ from other expert systems that depend on sets of rules, such as fuzzy logic, in that neural nets are capable of machine learning without rules. As discussed in [27], Neural nets can be classified as either supervised or unsupervised. Supervised neural nets are provided with a learning set in which both input and output are known. The Neural nets adjust their weights until the error between their output and the actual output is minimized. Then data from unknown inputs can be placed in the appropriate categories. In the case of Ref. [27], the problem of rotor imbalance of a multi-disk shaft is investigated with Neural Nets. The "input" to the neural net consists of conditions of imbalance; the "output" is represented by measured bearing reactions. A learning algorithm is then used to "train" the net to relate bearing reactions with presence (and possibly level) of imbalance. The authors have had recent success [28] in applying a related, previously-developed procedure for group classification, the linear discriminant operator referred to as "Fisher's Discriminant" [29], to vibration-based damage detection. The procedure falls into the general category of neural nets. The procedure requires data to be available from both the undamaged and damaged systems for training sets. It provides an estimate of the probability that new data fall within a finite number of sets (e.g., damaged and undamaged). An attractive feature of this statistical model is that it was applied to response data only. A pattern recognition analysis scheme, as applied to roller bearing condition monitoring, is presented in [8]. Features relating to the sum-frequency components of bearing defect frequencies and their harmonics are extracted. A linear discriminant operator is then developed to detect localized damage to bearing components. Unsupervised learning, in this context the case where data are available from only the undamaged system, has received little attention in the RM damage detection literature.

7. CONTRASTING THE RM AND CIVIL INFRASTRUCTURE APPLICATIONS

A general conclusion reached by the authors during the review reported above was that the application of vibration-based damage detection to RM has made the transition from a research topic to successful implementation by practicing engineers. In contrast, vibration-based damage detection in larger structures, such as bridges, has been studied for many years, but this application has, in most cases, not progressed beyond the research phase. By comparing and contrasting the RM application with the civil engineering infrastructure application it is hoped that some insight will be gained into the limitations of this technology for applications related to civil engineering infrastructure applications and how improvements might be made for this application.

A highway bridge will be the civil engineering structure used for this comparison, as this class of structure has been the focus of numerous vibration-based damage detection studies [10].

1. Motivation: Damage detection in bridges has been primarily motivated by the prevention of loss of life; damage detection in rotating machinery is motivated largely by economic considerations often related to minimizing production downtime. Clearly, there are exceptions where bridges are being monitored to facilitate timely and cost-effective maintenance and where failure of RM can have life-safety implications, as an example fracture of jet engine turbine blades.
2. Availability: Highway bridges are generally one-of-a-kind items with little or no data available from the damaged structure. RM are often available in large inventories with data available from both undamaged and damaged systems. It is much easier to build databases of damage-sensitive features from these inventories and, hence, supervised machine learning can be much more readily accomplished for RM.
3. Definition of Damage: For RM there are a finite number of well-defined damage scenarios that are being monitored and the possible locations of that damage are limited to a fairly small spatial region. Many bridge damage detection studies do not specifically define the damage that is to be monitored.
4. Operational Evaluation: In practical health-monitoring applications, measured vibration inputs are not applied to either class of system. Rotating machinery typically exhibits response to a harmonic-like input, while traffic tends to produce inputs that are typically assumed to be random in nature.
5. Data Acquisition: Because the approximate location of the damage is generally known, vibration test equipment for rotating machinery can consist of but a single sensor and a single-channel FFT analyzer. Monitoring of bridges is normally performed with a relatively few number of channels distributed over a relatively large spatial region. For damage ID on a highway bridge, 30-50 data acquisition channels represent a sparsely instrumented bridge. A permanent *in situ* data acquisition system for bridge structures can be represent a significant capital outlay and further funds will be needed to maintain such a system over extended periods of time.
6. Feature Selection: A well developed database of features corresponding to various types of damage has been developed by the RM community. Many of these features are qualitative in nature and have been developed by comparing vibration signatures from undamaged systems to signatures from systems with known types, locations and levels of damage. Many of the features observed in the vibration signatures of RM result from nonlinear behavior exhibited by the damaged system. Features used to identify damage in bridge structures are most often derived from linear modal properties such as resonant frequencies and mode shapes. These features are identified before and after damage and require a distributed system of sensors. Few studies report the development of damage-sensitive features for bridge structures based on nonlinear response characteristics.
7. Statistical Model Building: The RM literature reports many more studies that investigate the application of statistical pattern classifiers to the damage detection process than have been reported for civil engineering infrastructure applications. Rotating machinery is often sited in a relatively protected environment and operates under relatively consistent conditions. The primary sources of extraneous vibration inputs are other RM in the vicinity. Changes in damage-sensitive features caused by environmental and operational variability are significant and must be accounted for in bridge applications through statistical pattern classifiers. However, the literature shows little applications of this technology to bridge damage detection studies.

Clearly, the application of vibration-based damage detection to RM is a much more mature technology than that associated with large civil engineering infrastructure. Based on this comparison, the authors believe that the a pressing need for the civil engineering applications is to define a limited number of damage scenarios to be monitored that minimize the requirement for a distributed sensing system that must cover a large spatial area. Also, to account for variability in ambient traffic loading conditions and environmental variability, it is imperative that the civil engineering community adopt the statistical pattern classifier technology. Without this technology it will be difficult to determine if changes in dynamic properties are caused by damage or varying operation/environmental conditions.

8. SUMMARY AND CONCLUSIONS

In this review, the detection of damage or faults in rotating machinery is approached by interpreting the damage detection process as a problem in statistical pattern recognition. The proposed paradigm is very general and can be shown to encompass all vibration-based damage detection methods and applications. Key to the process is the selection of a suitable features sensitive to the damage as well as the application of a statistical model to quantitatively evaluate whether damage is in fact present and perhaps the location, type and degree of damage.

These features for rotating machinery were interpreted as either qualitative or quantitative. Quantitative features were further broken down by associating them with one of the following categories: Time-domain methods, Transformed-domain methods, and Time-frequency methods. Time-domain and time-frequency methods have their application in the investigation of rotating machinery faults exhibiting non-stationary vibration effects. Non-stationary effects are associated with machinery in which the dynamic response differs in the various phases of a machine cycle. Transformed-domain methods are generally associated with the detection of stationary faults.

The paper concludes by comparing the rotating machinery vibration-based damage detection process with vibration-based damage detection in large civil engineering infrastructure. This comparison notes many aspects of the rotating machinery applications that have allowed this technology to develop and mature to the point that it is used as standard practice by this industry. This comparison also identifies several improvements to the civil engineering applications that can be adopted directly from the rotating machinery fault-detection technology.

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